





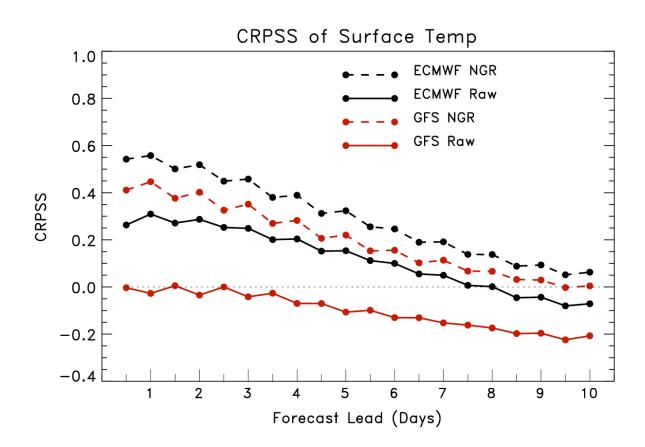
A comparison of calibrated T_{2m} probabilistic forecasts from GFS and ECMWF reforecasts

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Bottom-line messages

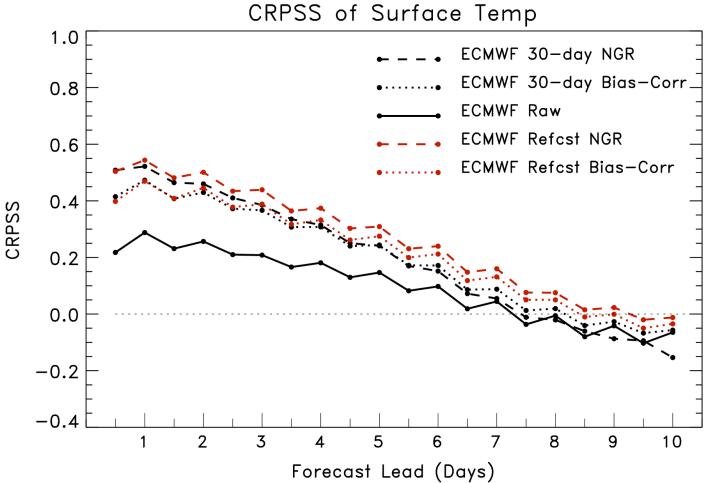
- (1) Calibrated GFS based on 1998 ensemble more skillful than probabilities from raw ECMWF ensemble.
- (2) Substantial improvement of ECMWF ensemble based on reforecasts; smaller amount than GFS, but still large.



Bottom-line messages

(3) 30-day bias corrections do a good job of correcting short-term forecasts. Somewhat less useful in medium range.

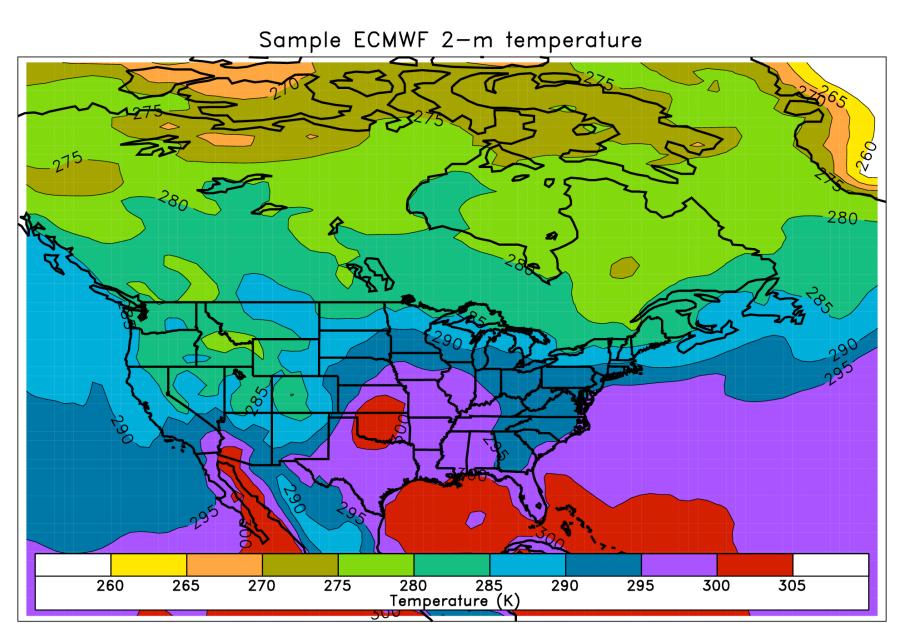
CRPSS of Surface Temp



ECMWF's reforecast data set

- Model: 2005 version of ECMWF model; T255 resolution.
- Initial Conditions: 15 members, ERA-40 analysis + singular vectors
- Dates of reforecasts: 1982-2001, Once-weekly reforecasts from 01 Sep 01 Dec, 14 total. So, 20*14 ensemble reforecasts = 280 samples.
- Data sent to NOAA / ESRL : T_{2M} ensemble over most of North America, excluding Alaska. Saved on 1degree lat / Ion grid. Forecasts to 10 days lead.

ECMWF domain sent to us for reforecast tests

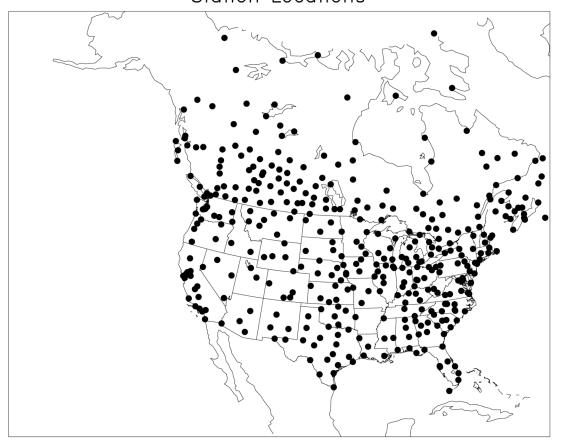


NOAA's reforecast data set

- Model: T62L28 NCEP GFS, circa 1998
- Initial States: NCEP-NCAR Reanalysis II plus 7 +/- bred modes.
- Duration: 15 days runs every day at 00Z from 19781101 to now. (<u>http://www.cdc.noaa.gov/people/jeffrey.s.whitaker/refcst/week2</u>).
- Data: Selected fields (winds, hgt, temp on 5 press levels, precip, t2m, u10m, v10m, pwat, prmsl, rh700, heating). NCEP/NCAR reanalysis verifying fields included (Web form to download at http://www.cdc.noaa.gov/reforecast). Data saved on 2.5-degree grid.
- Here, use only the subset of data overlapping with ECMWF reforecast data set.

Observation Locations

Station Locations



Uses stations from NCAR's DS472.0 database that have more than 96% of the yearly records available, and overlap with the domain that ECMWF sent us.

Calibration Procedure: "NGR" "Non-homogeneous Gaussian Regression"

- **Reference**: Gneiting et al., *MWR*, **133**, p. 1098
- Predictors: ensemble mean and ensemble spread
- Output: mean, spread of calibrated normal distribution

$$f^{CAL}(\overline{\mathbf{x}}, \sigma) \sim N(a + b\overline{\mathbf{x}}, c + d\sigma)$$

- Advantage: leverages possible spread/skill relationship appropriately. Large spread/skill relationship, c ≈ 0.0, d ≈1.0. Small, d ≈ 0.0
- **Disadvantage**: iterative method, slow...no reason to bother (relative to using simple linear regression) if there's little or no spread/skill relationship.

Training Data for

Non-homogeneous Gaussian Regression (all cross validated)

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• 01 Sep: 01 Sep, 08 Sep, 15 Sep
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• **08 Sep**: 01 Sep, *08 Sep*, 15 Sep, 22 Sep

• **15 Sep**: 01 Sep, 08 Sep, *15 Sep*, 22 Sep, 29 Sep

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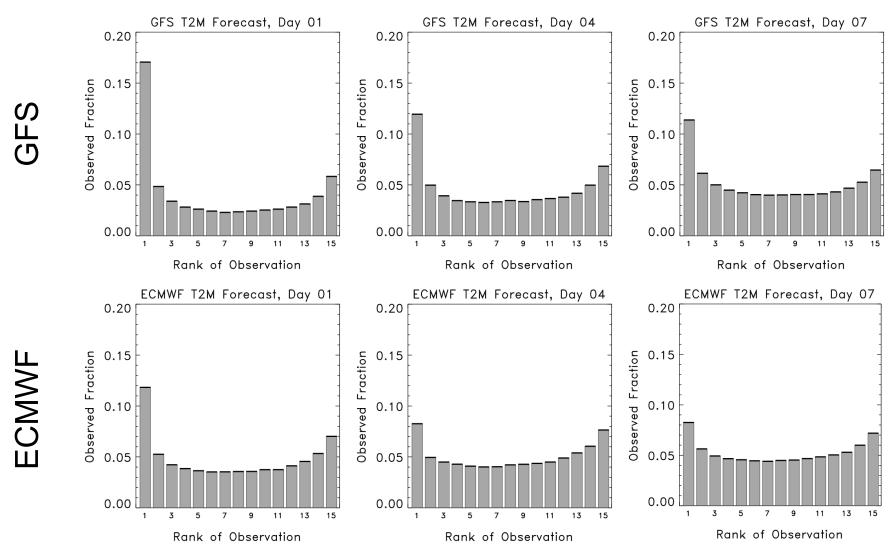
• **17 Nov**: 03 Nov, 10 Nov, *17 Nov*, 24 Nov, 01 Dec

24 Nov: 10 Nov, 17 Nov, 24 Nov, 01 Dec

• **01 Dec**: 17 Nov, 24 Nov, *01 Dec*

Use a centered training data set for weeks 3 - 12, uncentered for weeks 1, 2, 13, and 14

... but first, rank histograms



Members randomly perturbed by 1.0K to account for observation error; probably a bit small for GFS on its coarser 2.5° grid, which would make their histograms slightly more uniform. Ref: Hamill, *MWR*, **129**, p. 556.

Continuous Ranked Probability Score (CRPS) and Skill Score (CRPSS)

$$CRPS_{i,j,k}^{f} = \int_{-\infty}^{+\infty} \left[F_{i,j,k}(y) - F_{i,j,k}^{o}(y) \right]^{2} dy$$

 $i = 1, \dots, \# case days$

 $j = 1, \dots, \#$ years of reforecasts

 $k = 1, \dots, \#$ station locations

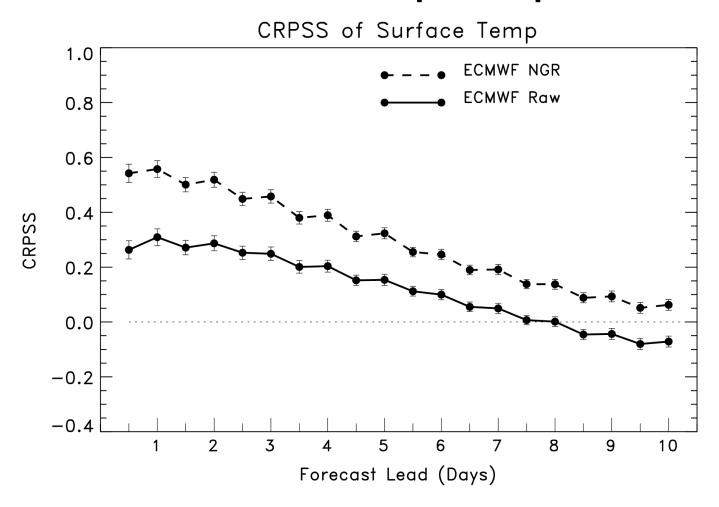
 $F_{i,j,k}(y)$ is forecast CDF at value y

 $F_{i,j,k}^{o}(y)$ is obs CDF at value y (Heaviside)

$$CRPSS = 1.0 - \frac{\overline{CRPS}^f}{\overline{CRPS}^c}$$

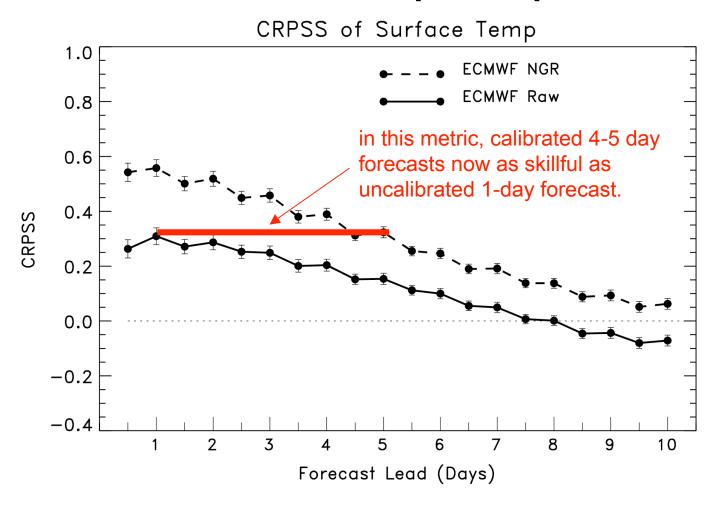
(This conventional way of calculating CRPSS exaggerates skill if some samples have more climatological spread than others. Will use a modified version where we calculate CRPSS separately for 8 different categories of climatological spread and then average them. See Hamill and Juras, January 2007, *QJRMS*, and Hamill and Whitaker (2007) *MWR*, to appear, tinyurl.com/290y8s)

ECMWF, raw and post-processed



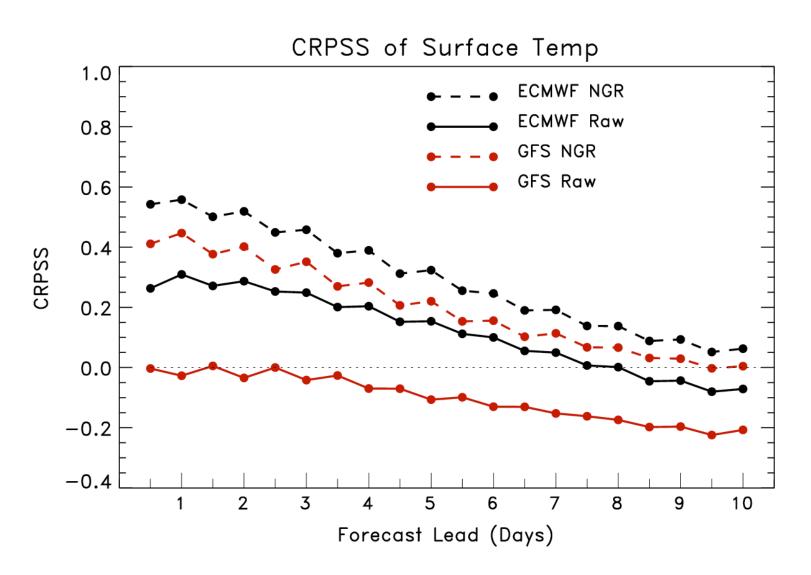
Small confidence intervals imply significant improvement at all leads

ECMWF, raw and post-processed

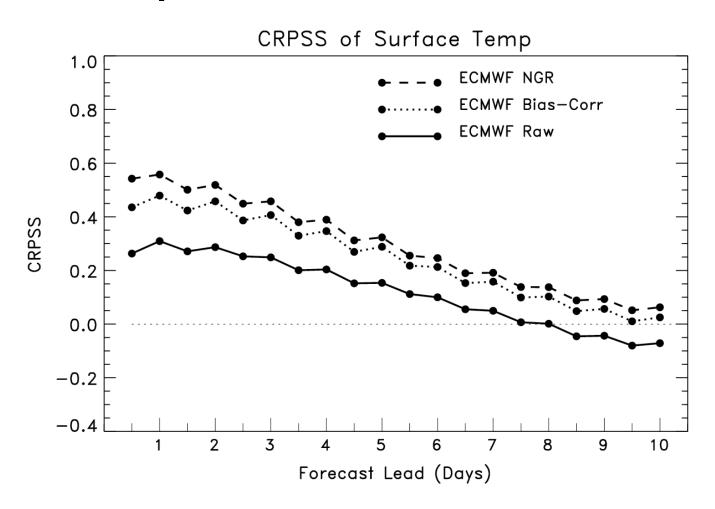


Small confidence intervals imply significant improvement at all leads

ECMWF and **GFS**

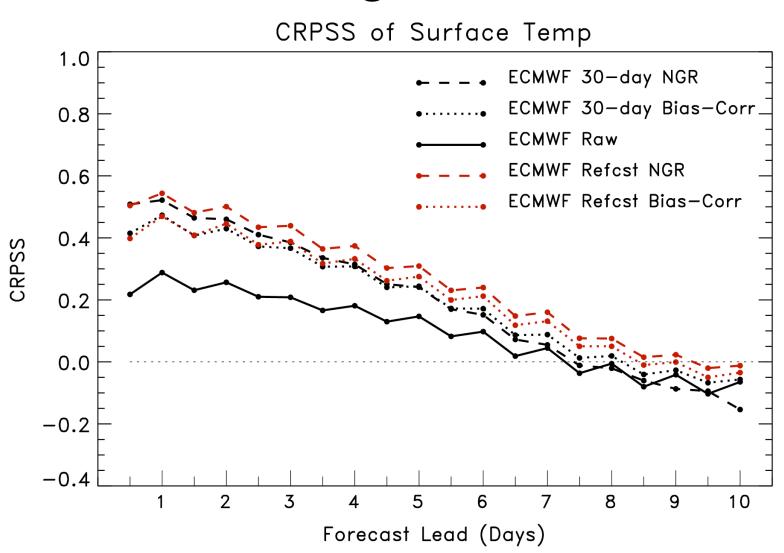


How much from simple bias correction?

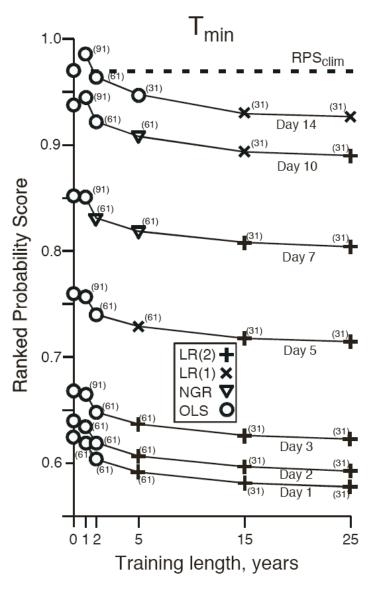


~ 60 percent of total improvement at short leads, 70 percent at longer leads.15

How much from short training data sets?

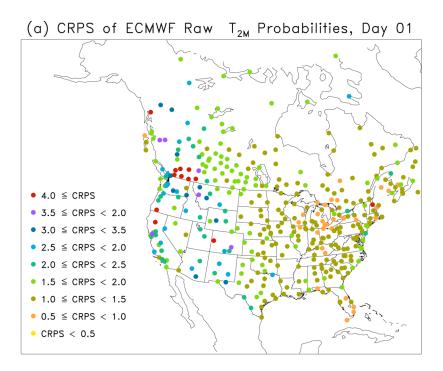


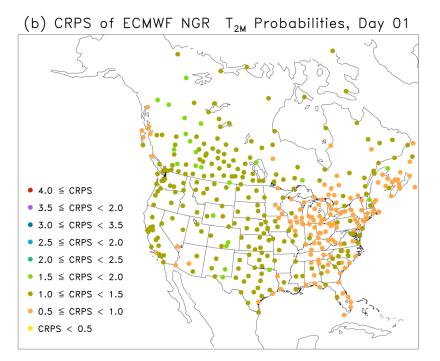
Results from GFS, T_{min}

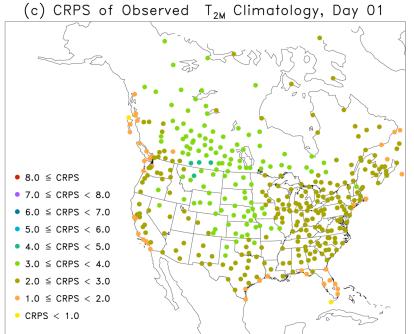


Are less optimistic results from short training data set with GFS reforecasts due to:

- poor model?
- use of full reforecast data set here, not subsample of 1x weekly?

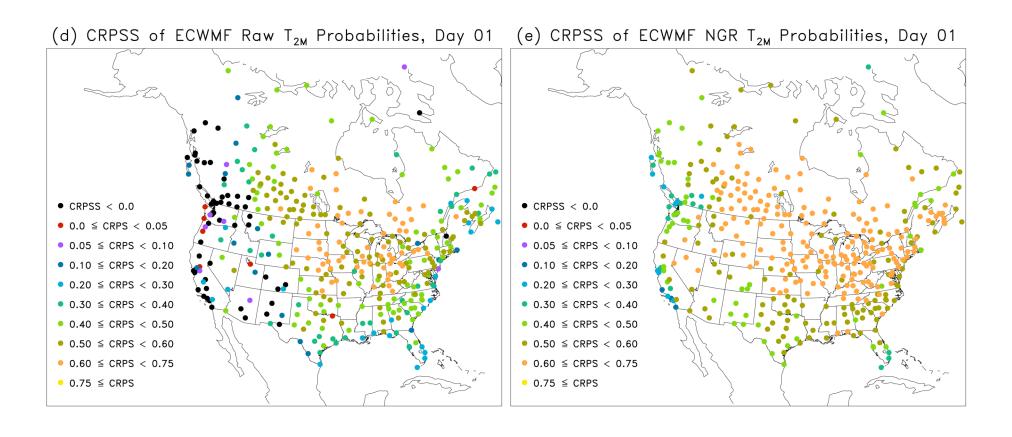




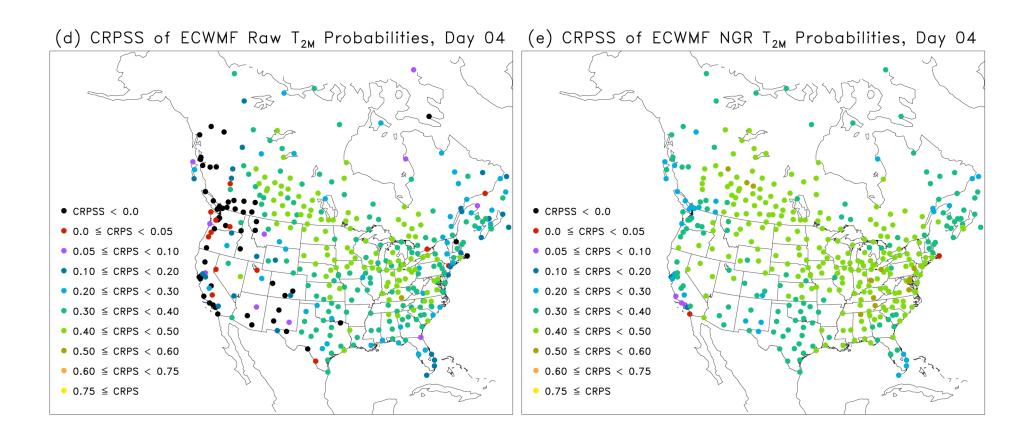


largest improvement at the stations with the highest original CRPS.

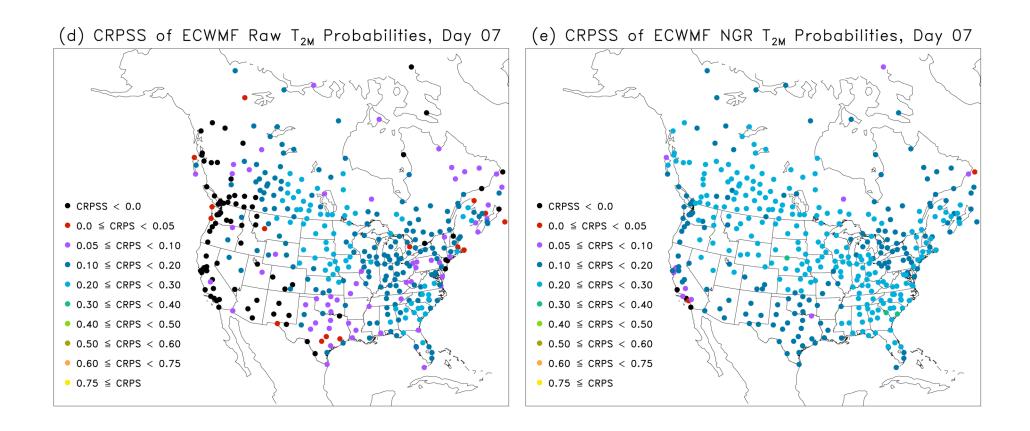
CRPSS, Day 1



CRPSS, Day 4

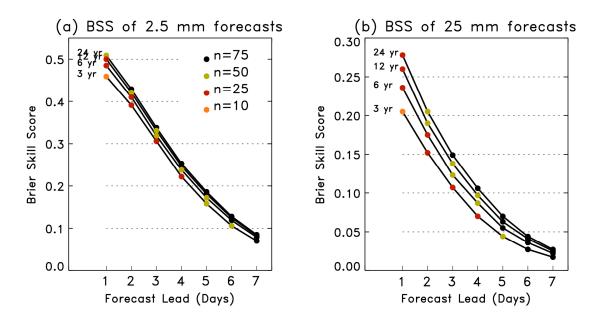


CRPSS, Day 7



Notes

 Same benefit to precipitation calibration, winds, other variables? Perhaps not, w/o more full reforecast data set.



more rare events, like heavy precipitation forecasting, tend to benefit more from long reforecast data sets.

Preliminary Conclusions

- Still substantial benefit to calibrating forecasts, even with a much better model than used in 1st-generation GFS reforecast.
- Old GFS + reforecast calibration » more skill than ECMWF uncalibrated.
- 30-day training does good job of calibration for short-term forecasts (consistent with previous NCEP results).
- Still need to test calibration of other variables (precipitation, wind speed, etc..)